

# Sensor-Based Decision Support for the Allocation of Patient Attendants in Hospitals

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**Abstract.** In hospitals, patient attendants are often necessary in order to closely monitor patients with high risk of self-endangering actions and reactions. However, such additional monitoring of patients is associated with high costs. In this paper, we describe a technical infrastructure for monitoring the patient's activities, which helps to assess whether an attendant should be requested. It was central to for us to use non-invasive sensors and to exploit a variety of patient data such as heart rate, micro-activity and oxygen saturation.

**Keywords.** clinical decision support; sensors; micro-activity; patient sitters

## 1. Introduction

Monitoring inpatients in hospitals is an ever-increasing challenge, as the amount of multimorbidity rises with aging population. Especially in acute care settings, many adverse events, such as delirium or a psychotic episode, are not related to the actual reason for being hospitalized. Patients who develop a delirium are disoriented, confused and/or unable to understand their current situation. In the elderly patients, a delirium can be superimposed on dementia. As a result, such patients might suddenly remove medical devices (such as venous access devices, tubes, catheters, electrodes, cables, etc.), they show stress reactions and/or attempt to stand up. Currently, in nursing practice, it is often difficult to predict whether and when a patient will develop such states that require close monitoring [1, 2]. There are certain known risk factors (such as age, drugs used, etc.), but often health professionals can only rely on their experience for taking any precautions or initiating any measures [3].

Attendants can be nursing trainees, medical students and non-health care professionals [4, 5]. Hospitals usually have a pool of such staff. Their job is to permanently watch the patient at risk and to intervene if required. On a normal ward, the options for interventions are limited to, e.g., calming down the patient by talking or calling additional nursing staff for help. Such additional monitoring of patients is

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associated with high costs. According to internal information from a Swiss university hospital (approximate bed size 900) yearly costs for patient attendants can sum up to 60 full-time nurse equivalents.

As the request for an attendant must be made several hours in advance, a positive decision can result in attendants sitting beside a sleeping patient, thus wasting resources. A case study at a hospital in Ohio reported that using a risk-based digital assessment tool for regularly allocating attendants can reduce the working hours without increasing the adverse events, indicating that there is potential in reducing costs [6].

Our goal was to provide and examine a sensor-based technical infrastructure monitoring the patient's activities, which might be helpful to assess whether an attendant should be requested. It was central for us to use non-invasive sensors and to exploit a variety of patient data such as heart rate, micro-activity and oxygen saturation.

## 2. Methods

### 2.1 *Review of the literature*

We conducted a literature research in Cinahl, PubMed, Web of Science and Google Scholar with a focus on the work of patient attendants, the decision process of employing them, sensors for detecting and preventing adverse events, and clinical decision support systems for allocating patient attendants. Keywords were identified in particular through preliminary discussions with stakeholders. These were then entered in various combinations:

- "sitter" or "attendants"
- ("sitters" OR "attendants") AND "risks"
- "constant observers"
- "constant observers" AND "risks"
- "inpatient" AND "fall detection"
- "patient monitoring" AND "fall detection"
- "mattress sensor care"
- "health data sensor"
- "patient monitoring sensor"
- "vital data sensor"

### 2.2 *Approaches considered*

In order to get insights into the actual work of patient attendants, a semi-structured questionnaire for interviews with attendants was prepared and eight interviews were conducted. The questions were related to the preparation and training for the job, contents of the tasks tackled, subjective assessments of the job, and opinions to the use of sensors in the context of the job. Inclusion criteria for the interview were: working at least half a year as patient attendant within the last two years, speaking German or English, working in a Swiss hospital, being of age.

To derive the requirements of a sensor-based monitoring system we developed several use-cases. In addition, we composed scribbles inspired from the Design-Thinking approach to visualize the processes itself and potential problems from the perspective of a patient attendant [7]. Based on that input, we implemented a web

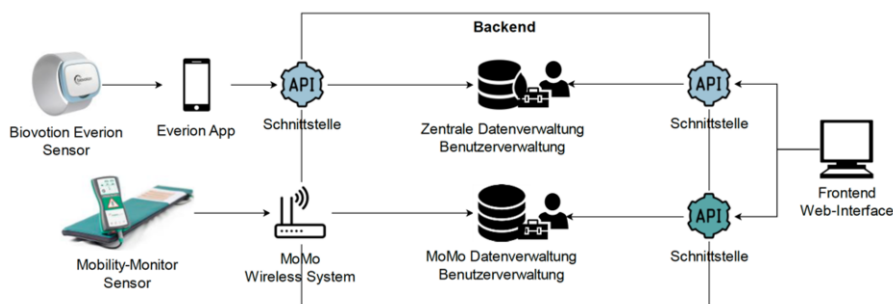
application to integrate the sensor data using the agile Scrum approach [8] in ten one-week sprints. We applied the JavaScript framework vue.js and loopback for the frontend and the backend, respectively.

### 3. Results

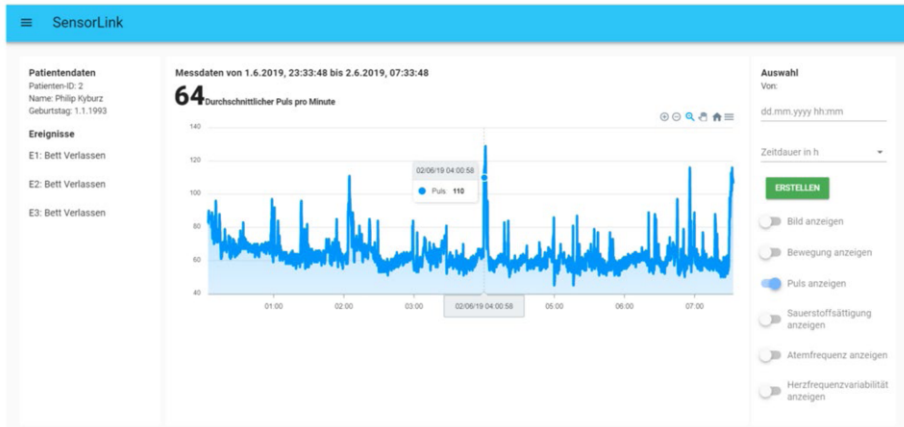
The results of our literature research showed a variety of definitions of the concept “patient attendant” [9,10]. Many different settings have been reported that require different forms of monitoring and interventions. This was corroborated by the eight interviews we have conducted. Some attendants just observed, others had to intervene, others used a lot of communication with the patient. In most cases, there were no trainings beforehand. Attendants had to deal with different medical conditions such as delirium, dementia, schizophrenia, suicidality, alcohol problems, etc. Interventions comprised calming down the patient, preventing the patient from standing up or make sure that a member of clinical staff is available swiftly. Approximately half of the deployments were futile because no interventions were required. The study participants indicated that sensors monitoring patient mobility and/or attempts to leave the bed might be beneficial.

We developed an evaluation matrix for sensors currently available on the market. Main criteria were measured parameters, running time, interfaces, how data is gathered (extend of invasiveness), costs, and certification as a medical device. Based on these attributes, we decided to use two complementary and nearly non-invasive sensors. One sensor is the *Mobility Monitor*<sup>TM</sup> (momo) of Compliant Concept, which monitors micro-movements of the patients in their bed by placing a sensor under the mattress. The system can detect accurately agitation and bed-leaving events. The other sensor (*Everion*<sup>TM</sup>) from Biovation is placed on the patients arm and measures pulse, skin temperature, oxygen saturation, respiratory rate, and some more parameters. For the momo sensor a REST API is available, for Everion a JAVA SDK has to be used in order to read the data.

The overall architecture of our prototype, called *SensorLink*, is given in Figure 1. Both sensors are queried every 10 seconds using the corresponding API. We combined the data of both sensors with clinical parameters into one single backend and provide interactive graphical outputs in order to assess whether a patient needs more monitoring. An example output of the front end is given in Figure 2. Interactivity in the graphical outputs is achieved by using the ApexCharts.js library for visualizations.



**Figure 1.** Overview on the prototypical sensor network system with two sensors (Everion and the Momo sensor) that provide data via different interfaces to the backend for display on a web interface.



**Figure 2.** The graphical user interface of the SensorLink system. Here, the pulse trajectory of one night is shown in the main panel. The peak pulse value is at 110 and the average value throughout the night was 64.

The data in Figure 2 was collected by installing the sensors and the system at the medical informatics laboratory in Bienne/Switzerland with the aim to validate our solution. The co-authors SG and PK slept two days each in the laboratory. Central events, such as leaving the bed, are given at the left panel of the graphical interface. In the right panel, different criteria can be selected, e.g., measurement period, micro-activity, pulse, heart frequency variability, etc. The results for this selection are provided in the main panel. The graphics are interactive and aligned with each other based on the time stamps, which allows to monitor several parameters at desired time points.

#### 4. Discussion

Currently, various sensor-based wearables, external sensors and even mobile video monitoring are available [11,12]. However, such solutions are frequently not apt for either reducing the amount of complications or for improving the decision efficiency regarding patient attendants' placements [13]. Especially, inappropriate decision and bad user experience associated with such additional systems pose serious problems [14]. To tackle these problems, non-invasive sensors data should be used together with rule-based reasoning and machine learning [15]. We have provided a first step in that direction.

The experiences in our project showed that it is rather cumbersome to individually integrate the diverse sensors. A decision-making system that uses many different sensors should use a comprehensive gateway solution that enables plug and play of those sensors. One commercial solution (<https://www.leitwert.ch>) provides an IoT middleware for managing and configuring such a gateway. It allows to collect data on a local server, which paves the way to use wearable medical devices in health care settings. Clocking of the different sensors is also a relevant issue, as the clock pulse can

vary between sensors. Further, it should be taken account that the amount of data generated by many sensors in short time intervals indicate that cloud-based solutions should be taken into consideration for scalability reasons.

We have gained first insights into the possible advantages of increased information on patients and suitable graphical summaries for the decision concerning placement of patient attendants. It is crucial, however, to prove the benefits of such a decision support tool for those who decide in practice. This requires a proper implementation study to evaluate the impact in a real-world setting. Central outcomes are acceptability, adoption, appropriateness, costs, feasibility, and sustainability [16]. Our goal is to conduct an implementation study with an extended version of our prototype, using a sensor gateway and machine learning components that do not just condense information but deliver advice whether a request of a patient attend is adequate or not.

## References

- [1] K. Harper, A. Barton, G. Arendts et al., Failure of falls risk screening tools to predict outcome: a prospective cohort study, *Emergency Medicine Journal* **35** (2018), 28–32.
- [2] J. De Wand, Delirium Screening: A Systematic Review of Delirium Screening Tools in Hospitalized Patients, *The Gerontologist* **55** (2015), 1079–1099.
- [3] F. Carr, The role of sitters in delirium: an update, *Can Geriatr J* **16** (2013), 22–36.
- [4] H. Tzeng, C. Yin, J. Grunawalt, Effective assessment of use of sitters by nurses in inpatient care settings, *Journal of Advanced Nursing* **64** (2008), 176–83.
- [5] M. Feil, S.C. Wallace. The Use of Patient Sitters to Reduce Falls: Best Practices, *Pa Patient Saf Advis* **11** (2014), 8–14.
- [6] D. Long, J. Dennis, Reducing sitter use in acute medicine while maintaining safety and quality, *Journal of Nursing Education and Practice* **9** (2018), 61–67.
- [7] M. Altman, T. Huang, J. Breland, Design Thinking in Health Care, *Preventing Chronic Disease* **15** (2018), E117.
- [8] H. Cervone, Understanding agile project management methods using scrum, *OCLC Syst Serv* **27** (2011), 18–22.
- [9] A. Schoenfisch, L. Pompeii, H. Lipscomb et al., An urgent need to understand and address the safety and well-being of hospital ‘sitters’, *American Journal of Industrial Medicine* **58** (2015), 1278–1287.
- [10] S. Solimine, J. Takeshita, D. Goebert et al., Characteristics of Patients with Constant Observers, *Psychosomatics* **59** (2018), 67–74.
- [11] T. Shany, S. Redmond, M. Narayanan et al., Sensors-Based Wearable Systems for Monitoring of Human Movement and Falls, *IEEE Sensors Journal* **12** (2012), 658–670.
- [12] P. Burtson, L. Vento, Sitter Reduction Through Mobile Video Monitoring: A Nurse-Driven Sitter Protocol and Administrative Oversight, *The Journal of Nursing Administration* **45** (2015), 363–372.
- [13] N. Kosse, K. Brands, J. Bauer et al., Sensor technologies aiming at fall prevention in institutionalized old adults: A synthesis of current knowledge, *International Journal of Medical Informatics* **82** (2013), 743–52.
- [14] M. Harrison, R. Koppel, S. Bar-Lev, Unintended Consequences of Information Technologies in Health Care: An Interactive Sociotechnical Analysis, *J Am Med Inform Assoc* **14** (2007), 542–9.
- [15] T. Syeda-Mahmood, Role of Big Data and Machine Learning in Diagnostic Decision Support in Radiology, *J Am Coll Radiol* **15** (2018), 569–576.
- [16] H. Christie, S. Bartels, L. Boots et al., A systematic review on the implementation of eHealth interventions for informal caregivers of people with dementia, *Internet Interv* **13** (2018), 51–59.